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Abstract

Non-functional or quality requirements such as usability, integrity and security play a significant part in the success of a software system. Non-functional requirements have more impact on software systems than the functional requirements. In the early phase of requirements engineering, the various design options for the functional behaviour (also known as the goal) of a software system are analysed and the perfect ones are chosen. In the goal analysis process, the goals that contribute to the maximum satisfaction of the non-functional requirements (also known as the softgoals) have to be selected. Whilst there have been a number of approaches for goal analysis, this paper focuses on the softgoals based optimisation model to select goals for a given i framework. This paper presents a multi-objective goal programming optimisation model to guide the goal analysis. A simulation for this approach was developed in Java Eclipse integrated with the IBM Cplex optimisation tool and evaluated with goal models such as Telemedicine, and Kids Youth counseling which were taken from the Requirements Engineering (RE) literature. The results of the evaluation show that the proposed optimal goal model approach is beneficial in the decision making of functional goals.*

Keywords: Requirements Engineering, Goal model, Softgoals, Multi-objective optimisation, Goal programming, i Framework.*

1 INTRODUCTION

To develop an efficient software system, stakeholders and designers need to identify several alternative design options. To do this, they require decision making methods which will assist them in selecting the designs most suitable for implementation. For modelling languages such as the Non-Functional Requirements(NFR) framework (Chung et al. 2000), the *i** framework (E.Yu 1995), Knowledge Acquisition in Automated Space (KAOS) (Dardenne et al. 1991), Tropos (Bresciani et al. 2004) and Goal- Oriented Requirement Language (GRL) (D. Amyot et al. 2010), many approaches have been developed to assit in the selection of alternative design options. These approaches include both qualitative and quantitative analysis, in which the qualitative or quantitative values are propagated, in either the top-down or bottom-up direction of the goal model. Lamsweerde(2009) proposed a lightweight quantitative alternative evaluation system for the KAOS framework. This approach uses certain values that are dependent on the system's specification. Affleck et al. (2012, 2013), proposed a process-oriented, lightweight, quantitative extension to the NFR framework to minimise the operationalisation. D.Amyot et al. (2010) presented the qualitative, quantitative and hybrid analysis procedure for the GRL model. Horkoff and Yu (2009) proposed an interactive qualitative analysis of goals for the *i** framework.

By and large, within the *i** framework, emphasis was placed upon on qualitative reasoning of softgoals, for analysis of the goal contributions (E.Yu 1995 and E.Yu et al. 2009). In the work presented by Chitra et al. (2015), a quantitative approach for identifying alternative design options has been proposed. This framework extends the *i** qualitative analysis (E.Yu et al. 2009) while overcoming some of the problems raised by it. The analysis used fuzzy based quantitative procedures to avoid the ambiguity problem that arises in qualitative analysis. Chitra et al.(2016) extended this quantitative approach by using a multi-objective optimisation model to identify alternative design options and model the impact of these designs upon the softgoals(Chitra et al. 2016). Doing so, influenced the necessity for quantitative goal models and presented a mathematical model for such models. It contributed a demonstration of how multi-objective optimisation models can be used to select the alternative designs for the case study of the London Ambulance System. Other works which were based upon optimisation were performed by Affleck et al. (2013) and Christopher et al.(2009). These works were applied to the NFR framework. Affleck (2013) used single objective optimisation, to minimise the operationalization and thereby maximize the overall satisfaction of the non-functional requirements of the system. Christopher (2009) presented an optimisation algorithm to find a set system functionalities that optimally satisfices a given set of non-functional requirements.

Given an *i** goal model with a number of actors and each actor having their own hierarchy of softgoals, goals and task level, the quantitative analysis proposed by Chitra et al. (2015), propagates the subjective values from the bottom up, to find the satisfaction scores of the softgoals for each goal or task. To avoid the subjective preferences used in the analysis, Chitra et al. (2016) has proposed multi-objective optimisation (Chitra et al. 2016). The objective functions are solved by using MATLAB Genetic algorithm to find the weights of the leaf softgoals, which are in turn used in the goals analysis. The analysis used is error-free, less intensive and scaled to a very large number of design alternatives. On the other hand, this process performs only partial optimisation of the goal model. The built optimisation model is based upon the leaf softgoals of an *i** framework and does not take into consideration the other softgoals within the hierarchy. As the alternative choices selected, are based upon the propagation of values throughout the entire hierarchy of softgoals, an optimal model still needs to be developed by taking into consideration all, of the softgoals within the hierarchy. The objective of this paper is to address this particular limitation, by developing an optimisation model that is based upon all of the softgoals and leaf softgoals for an *i** framework, presenting a complete optimisation model for an *i** framework.

This paper presents a multi-objective goal programming (MOGP) optimisation model, which can be used for identifying optimal design options amongst the alternatives whilst analysing the impact of the selected alternative design option upon the high-level softgoals. Given a quantitative goal model with different alternative choices to be selected, a set of objective functions based upon the leaf softgoals and softgoals is generated. To solve the objective functions by goal programming, an algorithm is developed and implemented in Java Eclipse integrated with the IBM Cplex optimisation tool. The solution to these objective functions is computed and used in the analysis so as to identify the optimal design choices. The techniques are illustrated using the Kids Youth Counseling (Horkoff and Yu 2009) and Telemedicine (E. Yu 2002) case studies. The case study simulations demonstrate a promising technique which can be used to support a sound decision making process for goal analysis in the requirements engineering (RE).

The remainder of the paper is structured as follows: Section 2 discusses the related works; Section 3 explains multi-objective optimisation in the *i** framework, building a complete optimisation model based upon softgoals of a given *i** goal model, introduction to multi-objective goal programming, and the formulation of these objective functions as Multi- Objective Goal Programming (MOGP); Section 4 explains the evaluation of this approach using case studies; and Section 5 concludes the paper.

2 RELATED WORKS

A great amount of research on the analysis of goal models using qualitative and quantitative methods has been proposed in RE literature. However, only a limited amount of this work uses the optimisation approach for goal analysis of the goal models. This section gives brief outline of the works that use optimisation and how this work is different from others.

William et al. (2011) proposed a multi-objective optimisation model for analysing the alternative design options to the KAOS framework. In this approach, the vector values for each leaf quality variable are simulated by applying probability distribution. The optimisation model does not take into account the non-functional requirements of the system. Affleck et al. (2013 and 2014) have applied linear programming to the NFR framework to minimise the operationalisations. Affleck applied single objective optimisation to maximise the overall system satisfaction of the non-functional elements of the system. D.Zowghi et al. (2014) have proposed a Multi Criteria Decision Analysis (MCDA) to analyse the conflicts that arise in NFR decision analysis and also applied TOPSIS as an MCDA technique to rank the alternatives. Chitra et al. (2016) has proposed a multi-objective optimisation for the *i** framework to support in the decision making of alternative design options. The main purpose of the optimal model was to find the values that are to be used in the goal analysis and thereby to avoid the analyst interaction. Chitra et al. (2016) has developed the optimal model based only on the leaf softgoals in the goal hierarchy, but has not taken into consideration the other softgoals in the goal hierarchy.

Since an alternative design selection depends upon all of the softgoals associated with it, an optimal model has to be developed by considering all of the softgoals. The work presented in this paper extends the work of Chitra et al. (2016) by means of developing an optimal goal model through taking into consideration all the softgoals, in the goal hierarchy.

3 COMPLETE OPTIMISATION MODEL FOR THE *i** FRAMEWORK WITH GOAL PROGRAMMING APPROACH

3.1 Multi-objective Optimisation in the *i** Framework

In Figure 1, for the Telemedicine goal model, the actor *Patient* and the actor *HealthcareProvider* has two alternatives, namely the tasks, *PatientCenteredCare* and *ProviderCenteredCare*. The chore of the requirement analyst is to select an alternative that contributes maximum satisfaction to the non-functional requirements (represented by softgoals). The alternative choices can be thought of as objectives of the system, and therefore the problem can be viewed as a multi-objective optimisation problem. The alternative, selected needs to maximise the satisfaction of the softgoals and hence form the maximisation optimisation problem. In general, a maximising multi-objective optimisation problem is written mathematically as:

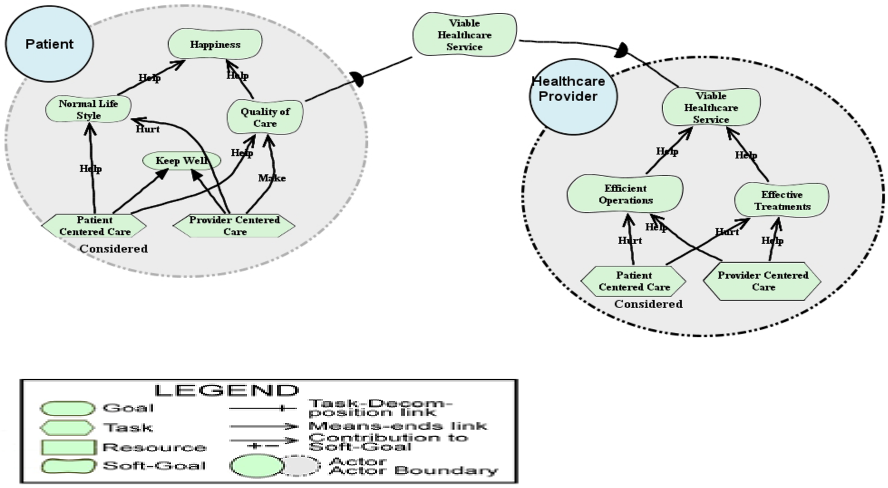

Figure 1. An Strategic Rationale Model: Telemedicine system (Adapted from E.Yu,2002)

$$\underset{x \in Y}{\text{Max}} \ [f1\ (x), f2\ (x), \ \ldots, fn(x)] \quad (1)$$

where *f1, f2,…., fn* are scalar functions and *Y* is the set of constraints.

3.2 Optimisation Model based on SoftGoals of an *i** goal model

To model generalised complete optimisation model of an *i** framework in terms of softgoals, consider the Strategic Rationale (SR) diagram as the directed graph G (N, A) with N as a set of nodes and A as set of arcs (Figure 2). The intentional elements softgoals, goals, and tasks in the SR diagram form the nodes of the directed graph G and the means-end, task-decomposition and operational contribution links form the arcs of the graph G.

An objective function for the optimisation model is formed in terms of the elements of the graph. For any node that is a leaf softgoal (LSG), there is a weight represented by ω_{LSGik}, meaning that the weight of the i^{th} leaf softgoal of the k^{th} actor. Additionally, any arc from a goal/task to a leaf softgoal that is an impact of goal/task is denoted by a triangular fuzzy number $\bar{C}_{Aj*LSGi,}$ denoting the impact of the j^{th} alternative (A) option on i^{th} leaf softgoal. The i^{th} leaf softgoal score is calculated from the weight of the i^{th} leaf softgoal and its impact for j^{th} alternative and is represented by $\bar{S}_{LSGij}$ (readers are directed to Chitra et al, 2015).

The score of i^{th} leaf softgoal for j^{th} alternative of k^{th} actor is given by

$$\bar{S}_{LSGijkt} = \bar{C}_{(Aj*LSGij)k} * \omega_{LSGijk} + \sum_{b=1}^{nd} (\bar{S}_{db} * \bar{I}_{db}) \quad (2)$$

where $\bar{S}_{db}$ is the score of its b^{th} dependent, $\bar{I}_{db}$ is the b^{th} dependent impact, '*t'* is the hierarchy level and for leaf softgoals, *t* is zero.

The score calculation of an i^{th} softgoal for j^{th} alternative of k^{th} actor at t^{th} level in the hierarchy is given by $\bar{S}_{SGijkt}$ (Chitra et al, 2015).

$$\bar{S}_{SGijkt} = \sum_{d=1}^{nc} (\bar{C}_{SGij*\ (SGdj|LSGdj)} * \bar{S}_{Ldjk(t-1)|SGdjk(t-1)}) + \sum_{b=1}^{nd} (\bar{S}_{d'b} * \bar{I}_{d'b}) \quad (3)$$

Where *'nc'* is the number of leaf softgoals and *'nd'* is the number of dependencies.

To find an optimal model based on softgoals, we need to write the softgoal score equation in terms of leaf softgoal score equation. To perform this, let us start with softgoals at level 1, which depends on the scores of leaf softgoals. The score of an i^{th} softgoal with '*nc'* children for j^{th} alternative of k^{th} actor at level $t=1$ is given by

$$\bar{S}_{SGijk} = (\bar{C}_{(SGij*LSG1j)} * \bar{S}_{LSG1jk}) + (\bar{C}_{(SGij*LSG2j)} * \bar{S}_{LSG2jk}) + \ldots + (\bar{C}_{(SGij*LSGncj)} * \bar{S}_{LSGncjk}) + \sum_{b=1}^{nd} (\bar{S}_{d'b} * \bar{I}_{d'b})$$

Replacing the scores of leaf softgoal with equation (2)

$$\bar{S}_{SGijk} = \{ (\bar{C}_{(SGij*LSG1j)} * \bar{C}_{(Aj*LSG1j)k} * \omega_{LSG1jk} + \sum_{b=1}^{nd} (\bar{S}_{db} * \bar{I}_{db})) + (\bar{C}_{(SGij*LSG2j)} * \bar{C}_{(Aj*LSG2j)k} * \omega_{LSG2jk} + \sum_{b=1}^{nd} (\bar{S}_{db} * \bar{I}_{db})) + \ldots\ldots + (\bar{C}_{(SGij*LSGncj)} * \bar{C}_{(Aj*LSGncj)k} * \omega_{LSGncjk} + \sum_{b=1}^{nd} (\bar{S}_{db} * \bar{I}_{db}))\} + \sum_{b=1}^{nd} (\bar{S}_{d'b} * \bar{I}_{d'b})$$

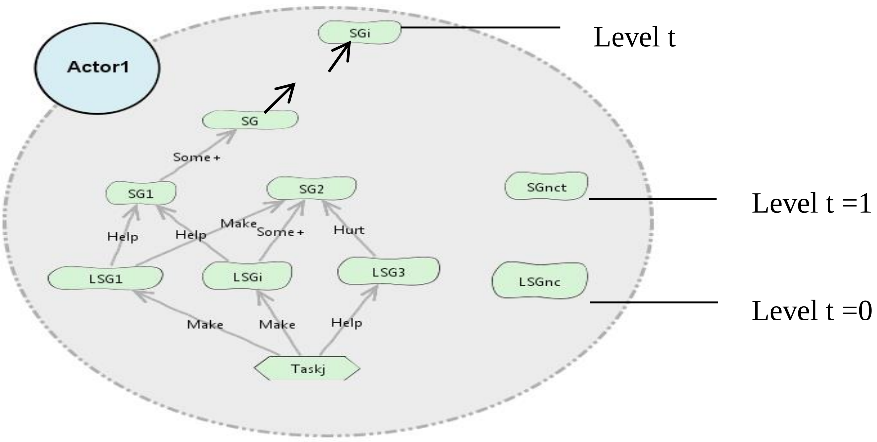

Figure 2. Directed Graph representation of a SR diagram

$$\bar{S}_{SGijk} = \{ (\bar{C}_{(SGij*LSG1j)} * \bar{C}_{(Aj*LSG1j)k} * \omega_{LSG1jk}) + (\bar{C}_{(SGij*LSG2j)} * \bar{C}_{(Aj*LSG2j)k} * \omega_{LSG2jk}) + \ldots\ldots + (\bar{C}_{(SGij*LSGncj)} * \bar{C}_{(Aj*LSGncj)k} * \omega_{LSGncjk} + \sum_{b=1}^{m} (\bar{S}_{db} * \bar{I}_{db}))\} + \sum_{b=1}^{nd} (\bar{S}_{db} * \bar{I}_{db}) + \sum_{b=1}^{nd} (\bar{S}_{db} * \bar{I}_{db}) + \ldots + \sum_{b=1}^{nd} (\bar{S}_{db} * \bar{I}_{db}) + \sum_{b=1}^{nd} (\bar{S}_{d'b} * \bar{I}_{d'b})$$

$$\bar{S}_{SGijk} = \sum_{d=1}^{nc} (\bar{C}_{SGij*LSGdj)} * * \bar{C}_{(Aj*LSGdj)k} * \omega_{LSGdjk}) + \sum_{y=1}^{nc} \sum_{b=1}^{nd} (\bar{S}_{dby} * \bar{I}_{dby}) + \sum_{b=1}^{nd} (\bar{S}_{d'b} * \bar{I}_{d'b}) \quad (4)$$

If there are '*m*' softgoals at level 1 and to obtain maximum softgoal score, the sum of softgoal scores have to be maximized. Therefore, the objective function is given by

$$Max\{ \bar{S}_{SG1jk} + \bar{S}_{SG2jk} + \ldots\ldots + \bar{S}_{SGmjk} \}$$

By replacing the softgoal score with equation (4)

$$\bar{S}_{SGijk} = Max \{ [\sum_{d=1}^{nc} (\bar{C}_{(SG1j*LSGdj)} * \bar{C}_{(Aj*LSGdj)k} * \omega_{LSGdjk}) + \sum_{y=1}^{nc} \sum_{b=1}^{nd} (\bar{S}_{dby} * \bar{I}_{dby}) + \sum_{b=1}^{nd} (\bar{S}_{d'b} * \bar{I}_{d'b})] + [\sum_{d=1}^{nc} (\bar{C}_{(SG2j*LSGdj)} * \bar{C}_{(Aj*LSGdj)k} * \omega_{LSGdjk}) + \sum_{y=1}^{nc} \sum_{b=1}^{nd} (\bar{S}_{dby} * \bar{I}_{dby}) + \sum_{b=1}^{nd} (\bar{S}_{d'b} * \bar{I}_{d'b})] + \ldots\ldots + [\sum_{d=1}^{nc} (\bar{C}_{(SGmj*LSGdj)} * \bar{C}_{(Aj*LSGdj)k} * \omega_{LSGdjk}) + \sum_{y=1}^{nc} \sum_{b=1}^{nd} (\bar{S}_{dby} * \bar{I}_{dby}) + \sum_{b=1}^{nd} (\bar{S}_{d'b} * \bar{I}_{d'b})] \}$$

$$\bar{S}_{SGijk} = Max\{ [\sum_{i=1}^{m} \sum_{d=1}^{nc} (\bar{C}_{(SGij*LSGdj)} * \bar{C}_{(Aj*LSGdj)k} * \omega_{LSGdjk})] + \sum_{i=1}^{m} \sum_{y=1}^{nc} \sum_{b=1}^{nd} (\bar{S}_{dbyi} * \bar{I}_{dbyi}) + \sum_{i=1}^{m} \sum_{b=1}^{nd} (\bar{S}_{d'bi} * \bar{I}_{d'bi}) \}$$

The score of any softgoal at hierarchy level t >1 is obtained by multiplying its impact with child score. This way it propagates upwards. Therefore, for any softgoal at level '*t'*, the score can be generalised as

$$\bar{S}_{SGijk} = Max \prod_{l=1}^{t} \bar{C}_{SGijl} \sum_{i=1}^{m} \{ [\sum_{d=1}^{nc} (\bar{C}_{(SGij*LSGdj)} * \bar{C}_{(Aj*LSGdj)k} * \omega_{LSGdjk})] + \sum_{i=1}^{m} \sum_{y=1}^{nc} \sum_{b=1}^{nd} (\bar{S}_{dbyi} * \bar{I}_{dbyi}) + \sum_{i=1}^{m} \sum_{b=1}^{nd} (\bar{S}_{d'bi} * \bar{I}_{d'bi}) \}$$

Hence, the objective function to obtain optimal weight of the leaf softgoals that maximise the top softgoal scores for the j^{th} alternative is

$$\bar{S}_{SGijk} = Max\prod_{l=1}^{t}\bar{C}_{SGijl}\{ \sum_{i=1}^{m} [\sum_{d=1}^{nc}(\bar{C}_{(SGij*LSGdj)} * \bar{C}_{(Aj*LSGdj)k} * \omega_{LSGdjk})] + \sum_{i=1}^{m}\sum_{y=1}^{nc}\sum_{b=1}^{nd}(\bar{S}_{dbyi} * \bar{I}_{dbyi}) + \sum_{i=1}^{m}\sum_{b=1}^{nd}(\bar{S}_{d'bi} * \bar{I}_{d'bi})\} \quad (5)$$

Such that

$0 \leq \omega_{LSGd} \leq 100$ for $d = 1$ to nc

The objective function(Equation 5) takes into consideration both the Strategic Dependency (SD) and Strategic Rationale (SR) model of an *i** framework. To generate a simple optimal objective function, we are only optimizing SR without considering SD. So, the objective function for an *i** framework by considering only SR is given by Equation 6 as below:

$$\bar{S}_{SGijk} = Max \prod_{l=1}^{t}\bar{C}_{SGijl}\sum_{i=1}^{m}\sum_{d=1}^{nc}(\bar{C}_{(SGij*LSGdj)} * \bar{C}_{(Aj*LSGdj)k} * \omega_{LSGdjk}) \quad (6)$$

Such that

$0 \leq \omega_{LSGd} \leq 100$ for $d = 1$ to nc

If there are '*n*' alternatives for an actor, then there are '*n*' objective functions as follows:

$$\left.\begin{aligned}
f_1(\omega_L) &= \bar{S}_{SGi1k} = Max\prod_{l=1}^{t}\bar{C}_{SGijl}\sum_{i=1}^{m}\sum_{d=1}^{nc}(\bar{C}_{(SGi1*LSGd1)} * \bar{C}_{(A1*LSGd1)k} * \omega_{LSGd1k})\\
f_2(\omega_L) &= \bar{S}_{SGi2k} = Max\prod_{l=1}^{t}\bar{C}_{SGijl}\sum_{i=1}^{m}\sum_{d=1}^{nc}(\bar{C}_{(SGi2*LSGd2)} * \bar{C}_{(A2*LSGd2)k} * \omega_{LSGd2k})\\
&\dots\dots\\
&\dots\dots\\
f_n(\omega_L) &= \bar{S}_{SGink} = Max\prod_{l=1}^{t}\bar{C}_{SGijl}\sum_{i=1}^{m}\sum_{d=1}^{nc}(\bar{C}_{(SGij*LSGdj)} * \bar{C}_{(Aj*LSGdj)k} * \omega_{LSGdjk})
\end{aligned}\right\} \quad (7)$$

Such that

$0 \leq \omega_{LSGd} \leq 100$ for $d = 1$ to nc

Likewise, for each actor in the SR model, objective functions are generated. A cumulative objective functions can be generated if all the actors have same type of alternatives. In a goal model with '*p*' number of actors, the objective function for a j^{th} alternative option is given by:

$$\begin{aligned}
f_j(\omega_L) = Max \{&\prod_{l=1}^{t}\bar{C}_{SGijl}\sum_{i=1}^{m}\sum_{d=1}^{nc}(\bar{C}_{(SGij*LSGdj)} * \bar{C}_{(Aj*LSGdj)1} * \omega_{LSGdj1})\\
&+ \prod_{l=1}^{t}\bar{C}_{SGijl}\sum_{i=1}^{m}\sum_{d=1}^{nc}(\bar{C}_{(SGij*LSGdj)} * \bar{C}_{(Aj*LSGdj)2} * \omega_{LSGdj2})\\
&+ \dots + \dots + \prod_{l=1}^{t}\bar{C}_{SGijl}\sum_{i=1}^{m}\sum_{d=1}^{nc}(\bar{C}_{(SGij*LSGdj)} * \bar{C}_{(Aj*LSGdj)p} * \omega_{LSGdjp})\}
\end{aligned}$$

In short the function is given by:

$$f_j(\omega_L) = Max \sum_{k=1}^{p}\prod_{l=1}^{t}\bar{C}_{SGijl}\sum_{i=1}^{m}\sum_{d=1}^{nc}(\bar{C}_{(SGij*LSGdj)} * \bar{C}_{(Aj*LSGdj)k} * \omega_{LSGdjk}) \quad (8)$$

Therefore the objective functions for a goal model with '*n*' number of alternatives are given by

$$\left.\begin{aligned}
f_1(\omega_L) &= Max \sum_{k=1}^{p}\prod_{l=1}^{t}\bar{C}_{SGijl}\sum_{i=1}^{m}\sum_{d=1}^{nc}(\bar{C}_{(SGi1*LSGd1)} * \bar{C}_{(A1*LSGd1)k} * \omega_{LSGd1k})\\
f_2(\omega_L) &= Max \sum_{k=1}^{p}\prod_{l=1}^{t}\bar{C}_{SGijl}\sum_{i=1}^{m}\sum_{d=1}^{nc}(\bar{C}_{(SGi2*LSGd2)} * \bar{C}_{(A2*LSGd2)k} * \omega_{LSGd2k})\\
&\dots\dots\\
&\dots\dots\\
f_n(\omega_L) &= Max \sum_{k=1}^{p}\prod_{l=1}^{t}\bar{C}_{SGijl}\sum_{i=1}^{m}\sum_{d=1}^{nc}(\bar{C}_{(SGin*LSGdn)} * \bar{C}_{(An*LSGdn)k} * \omega_{LSGdnk})\\
&\text{Subject to:}\\
&0 \leq \omega_{LSGdk} \leq 100 \quad \text{for } d = 1 \text{ to } nc \text{ and } k = 1 \text{ to } p\\
&0 \leq \bar{C}_{Aj*LSGdk} * \omega_{LSGdk} \leq 100 \text{ for } d = 1 \text{ to } nc, j = 1 \text{ to } n \text{ and } k = 1 \text{ to } p
\end{aligned}\right\} \quad (9)$$

In general, the multiple objective functions are given by following equation:

$$Max\ [\ f_1(\omega_L), f_2(\omega_L),\ ...., f_n(\omega_L)]$$

$$with\ \omega_L\ \epsilon\ Y \qquad (10)$$

where $n > 1$ and Y is the set of constraints defined.

A great strategy to solve the above type of multi-objective linear programming (MOLP) is by goal programming (Lidiane et al. 2010 and Caramia et al. 2008). The following section describes goal programming approach to solve multiple objectives.

3.3 Multi-Objective Goal Programming (MOGP)

This section gives a brief introduction to multi –objective goal programming.

Optimisation problems usually includes circumstances of minimizing and/or maximizing several conflicting functions simultaneously. Such cases are specified as multi-objective optimisation problems, also known as multicriteria, multiperformance, or vector optimizations. Among different approaches used to solve multi-objective functions, goal programming proposed by Charnes and Cooper (1957), is a great strategy which can be used to solve multi-objective problems by assigning multiple goals (Caramia et al. 2008).

The goal programming requires that the user designates targets/goals for each objective they need to meet. The main concept in goal programming is to compute solutions that achieve a predefined goal for one or more objective functions. Thus, goal programming involves expressing a set of goals $g=[g_1, g_2,...,g_n]$ with a set of objectives, $f(x) = [f_1(x), f_2(x), ..., f_n(x)]$. The optimization problem can be formulated as goal

$$f_i(x) = g_i\ ,\ i = 1,..., n;\ x\ \epsilon\ \Omega, \qquad (11)$$

where Ω is the feasible search region.

3.4 Formulation of the *i** framework as a Multi-Objective Goal model

The Goal programming method requires that the decision maker specifies a goal or a target for each objective (a set of goals for an MOLP) that he/she wishes to achieve. The objective of goal programming is to obtain a predefined target for one or more objective functions. If no solution reaches predefined targets in all of the objective functions, then preferred solutions that minimize the deviations from those goals, are to be identitfied. Presented below is a formal description of the optimisation problem.

The MOLP of an *i** framework as given by equation 10 is

$$Max\ \ f(\omega_L) = [\ f_1\omega_L, f_2\omega_L,\ ...., f_n\omega_L]$$

$$with\ \omega_L\ \ Y$$

where $n > 1$ and Y is the set of constraints defined.

In goal programming, the user chooses the goal value g, for every objective function and the task is then focussed to make each objective $f_i\omega_L$ as close to its goal g_i as possible, subject to the condition that the resulting solution is feasible($\omega_L\ \epsilon\ \Omega$). The optimisation problem can be formulated as follows:

$$\text{goal}\ \ f_i\omega_L = g_i,\ i= 1,2,\dots,n;\ \omega_L\ \epsilon\ \Omega, \qquad (12)$$

where Ω is the feasible region.

Two positive deviation variables, v_i^-, v_i^+ are introduced representing the under and over achievement of the i^{th} goal g_i for the i^{th} objective $f_i\ \omega_L$ $(i=1,2,...,n)$ respectively. The objective now is to minimize the sum of the deviations $(v_i^- + v_i^+)$, so that the optimal solution is minimally distant from the goal, in either direction. The optimisation problem is now remodelled as follows

$$\left.\begin{array}{l}\min\limits_{\omega_L, v1-, v1+, \ldots\ldots, vn-, vn+} v_1^- + v_1^+ + \ldots\ldots + v_n^- + v_n^+ \\ \text{s.t} \\ f_1\omega_L + v_1^- - v_1^+ = g_1, \\ f_2\omega_L + v_2^- - v_2^+ = g_2, \\ \ldots \\ \ldots \\ f_n\omega_L + v_n^- - v_n^+ = g_n, \\ v_1^-, v_1^+, \ldots\ldots\ldots, v_n^-, v_n^+ \geq 0 \\ \omega_L \epsilon\, \Omega \end{array}\right\} \quad (13)$$

To perform direct comparisons of the objectives, a requirements analyst can use weighted or non-pre-emptive goal programming. To indicate the relative importance of the objectives, all of the deviations between the objectives and goals are multiplied by weights and are expressed as a standard optimisation problem using the following formulation

$$\left.\begin{array}{l} Min\ v = \sum_{i=1}^{n} \alpha_i v_i^- + \beta_i v_i^+ \\ \text{Subject to} \\ f_i\omega_L + v_i^- - v_i^+ = g_i,\ i = 1,2, \ldots., n \\ v_i^-, v_i^+ \geq 0,\ \ \omega_L \epsilon\, \Omega \end{array}\right\} \quad (14)$$

MOGP demands that goals are assigned for each objective and a favoured solution is designated to be one which minimises the deviations of the goals.

Let us assume that the goals $g = (g_{1,\ldots\ldots,} g_n)$ are given for the objective functions $f(\omega_L) = (f_1\omega_L, \ldots\ldots.., f_n\omega_L)$ by the RE analyst, and a decision variable, $\omega_{L^*}\, \varepsilon\, W_L$ in the MOLP problem, is sought so that the objective functions, $f^*(\omega_L) = (f_1^*\omega_L, \ldots\ldots.., f_n^*\omega_L)$, are as close as possible to the goals, $g = (g_{1,\ldots\ldots,} g_n)$. The deviation between $f^*(\omega_L)$ and g is defined as a deviation function $D(f(\omega_L), g)$. The MOGP is now defined as an optimisation problem as follows

$$\min_{\omega_{L^*}\varepsilon\, W_L} D(f(\omega_L), g) \quad (15)$$

s.t

$$\omega_{L^*}\, \varepsilon\, W_L = \{\ \omega_{L^*}\, \varepsilon\, R^n\ |Y\}$$

The deviation function $D(f(\omega_L), g)$ is a maximum of deviations of individual goals

$$D(f(\omega_L), g) = Max\ \{\ D_1(f_1(\omega_L), g_1), \ldots\ldots\ldots, D_n(f_n\ (\omega_L), g_n)\} \quad (16)$$

From equation 13 and 14, the min-max approach is applied the GP problem.

$$\min_{\omega_{L^*}\varepsilon\, W_L} max\{D_1(f_1(\omega_L), g_1), \ldots\ldots\ldots, D_n(f_n\ (\omega_L), g_n)\} \quad (17)$$

By introducing an auxiliary variable γ, equation 17, is now written as linear program problem as

$$\left.\begin{array}{l} \min\limits_{\omega L} \gamma \\ s.t \\ D_1(f_1(\omega_L), g_1) \leq \gamma \\ D_2(f_2(\omega_L), g_2) \leq \gamma \\ \ldots \\ \ldots \\ D_n(f_n(\omega_L), g_n) \leq \gamma \\ \omega_L\ \epsilon\, Y \end{array}\right\} \quad (18)$$

4 EVALUATION OF ALTERNATIVES WITH SOFTGOAL OPTIMISATION

A simulation for the complete optimisation model, based goal programming, was developed and implemented in Java Eclipse integrated with the IBM Cplex optimisation tool (Figure 3). The input to the simulation was a set of objective functions for a given *i** framework and the outputs were the weights of the leaf softgoals of the given model. These weights are in turn used in the goal analysis to find the alternatives that maximises the top softgoals of the given *i** model. The MOGP model for an *i** framework was evaluated using the goal models from the existing RE literature: Youth Counseling (Horkoff et al. 2009), Meeting Scheduler System (Lamsweerde et al. 2004), London Ambulance System (You, Z., 2004) and Telemedicine (Yu 2002). To demonstrate this approach within the space restrictions, the adapted Youth Counseling System and Telemedicine goal models are used in this paper.

4.1 Deriving Objective Functions for the Actors

The following illustrates the derivation of multi-objective functions in terms of goal programming for the Youth Counseling case study (Figure 4). The alternatives in all three actors are

- Kids Use CyberCafe/Portal/Chat Room
- Kids Use TextMessaging

In this case, the problem is to select an alternative that achieves maximum satisfactions for softgoals *GetEffectiveHelp*, *Happiness* and *HelpKids* of actors *Kids and Youth*, *Counsellor* and *Organisation* respectively. Chitra et al. (2015) has proposed a quantitative analysis be applied for such types of problems. In this analysis, the weights for the leaf softgoals which are assigned by the analyst, are subjective to the analyst. To avoid this subjective preference, the weights are obtained by the MOGP optimisation model. These weights are in turn used in the analysis to select an alternative that yields maximum satisfaction of the top softgoals. Now by considering the first actor *Kids and Youth:*

Score of the top softgoal *GetEffectiveHelp* for alternative *UseTextMessaging* is

$$\begin{aligned} S_{GetEffectiveHelp} &= Help * S_{Comfotableness} + Help * S_{Anonymity} + Help * S_{Immediacy} \\ &= 0.64 * S_{Comfotableness} + 0.64 * S_{Anonymity} + 0.64 * S_{Immediacy} \\ &= 0.64 * [\, 0.64 * \omega_1] + 0.64 * [\, 0.64 * \omega_2] + 0.64 * [\, 0.16 * \omega_3] \\ &= 0.4096 * \omega_1 + 0.4096 * \omega_2 + 0.1024 * \omega_3 \end{aligned}$$

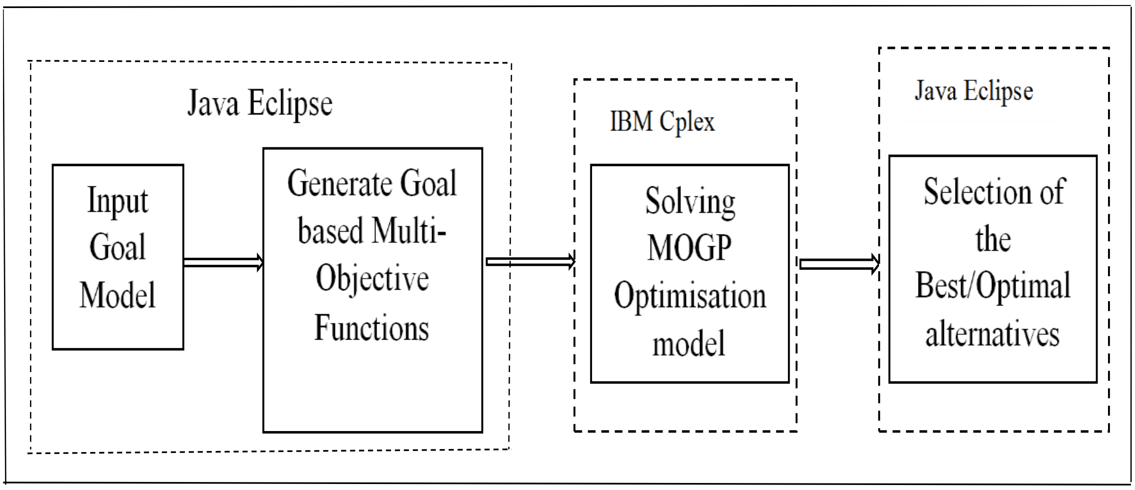

Figure 3: Scheme of the Multi-Objective Goal Programming Soft goal Optimisation and alternative selection

Therefore, the objective function for the alternative *UseTextMessaging* in terms of the top softgoal *GetEffectiveHelp* is

$$F_{Text}(\omega) = Max\{0.4096 * \omega_{11} + 0.4096 * \omega_{21} + 0.1024 * \omega_{31}\}$$

Similarly, the Score of the top softgoal *GetEffectiveHelp* for alternative *KidsUseCyberCafe* is

$$\begin{aligned} S_{GetEffectiveHelp} &= Help * S_{Comfotableness} + Help * S_{Anonymity} + Help * S_{Immediacy} \\ &= 0.64 * S_{Comfotableness} + 0.64 * S_{Anonymity} + 0.64 * S_{Immediacy} \\ &= 0.64 * [\ 0.64 * \omega_1] + 0.64 * [\ 0.16 * \omega_2] + 0.64 * [\ 0.8 * \omega_3] \\ &= 0.4096 * \omega_1 + 0.1024 * \omega_2 + 0.512 * \omega_3 \end{aligned}$$

Therefore, the objective function for the alternative *KidsUseCyberCafe* in terms of the top softgoal *GetEffectiveHelp* is

$$F_{CyberCafe}(\omega) = Max\{0.4096 * \omega_{11} + 0.1024 * \omega_{21} + 0.512 * \omega_{31}\}$$

Similarly, the objective functions for the other two actors are obtained. For the actor Organisation, the objective functions are

$$F_{Text}(\omega) = Max\{\ 0 * \omega_{12} + 0.1024 * \omega_{22} + 0.1074 * \omega_{32}\}$$
$$F_{CyberCafe}(\omega) = Max\{\ 0.4096 * \omega_{12} + 0.1024 * \omega_{22} + 0.2685 * \omega_{32}\}$$

For the actor Counsellor, the objective functions are

$$F_{Text}(\omega) = Max\{0 * \omega_{13}\}$$
$$F_{CyberCafe}(\omega) = Max\{\ 0.0655 * \omega_{13}\}$$

Since the alternatives are same in all three actors we have cumulative objective functions as below

$$\left.\begin{aligned} &F_{Text}(\omega) = Max\{\ 0.4096 * \omega_{11} + 0.4096 * \omega_{21} + 0.1024 * \omega_{31} + 0 * \omega_{12} + 0.1024 * \omega_{22} \\ &\quad + 0.1074 * \omega_{32} + 0 * \omega_{13}\} \\ &F_{CyberCafe}(\omega) = Max\{\ 0.4096 * \omega_{11} + 0.1024 * \omega_{21} + 0.512 * \omega_{31} + 0.4096 * \omega_{12} \\ &\quad + 0.1024 * \omega_{22} + 0.2685 * \omega_{32} + 0.0655 * \omega_{13}\} \\ &\qquad \textit{Subject to} \\ &\qquad\qquad 0 \leq \omega_{dk} \leq 100 \quad \textit{for } d = 1 \textit{ to } 3 \textit{ and } k = 1 \textit{ to } 3 \end{aligned}\right\} \quad (19)$$

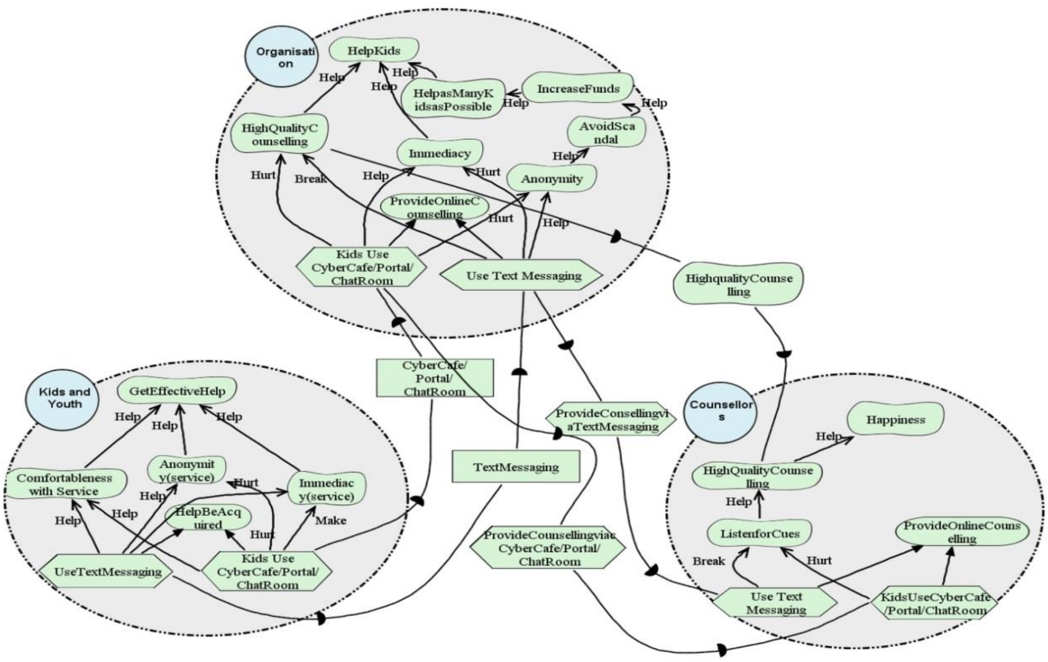

Figure 4. SR Model for Youth Counseling (adapted from Horkoff and Yu, 2009)

Similarly for Telemedicine (Figure 1) goal model, the objective functions are given as

$$\left.\begin{array}{l} F_{PatientCenteredCare}(\omega) = Max\{\, 0.4096 * \omega_{11} + 0.4096 * \omega_{21} + 0.1024 * \omega_{12} + 0.1024 * \omega_{22} \,\} \\ F_{ProviderCenteredCare}(\omega) = Max\{\, 0.1024 * \omega_{11} + 0.512 * \omega_{21} + 0.4096 * \omega_{12} + 0.4096 * \omega_{22} \,\} \\ \qquad \text{Subject to} \\ 0 \le \omega_{dk} \le 100 \quad \text{for } d = 1 \text{ to } 2 \text{ and } k = 1 \text{ to } 2 \end{array}\right\} \quad (20)$$

4.2 Obtaining Weights by MOGP

For Youth counseling case study, by considering the goals for each objective functions to be equal to

$$F_{Text}(\omega) = 80 \quad \text{and } F_{CyberCafe}(\omega) = 90$$

The optimisation problem with the auxiliary variable γ :

$$\min_{\omega L} \gamma$$
$$s.t$$
$$0.4096 * \omega_{11} + 0.4096 * \omega_{21} + 0.1024 * \omega_{31} + 0 * \omega_{12} + 0.1024 * \omega_{22} + 0.1074 * \omega_{32} + 0 * \omega_{13} - 80 \le \gamma$$
$$0.4096 * \omega_{11} + 0.1024 * \omega_{21} + 0.512 * \omega_{31} + 0.4096 * \omega_{12} + 0.1024 * \omega_{22} + 0.2685 * \omega_{32} + 0.0655 * \omega_{13} - 90 \le \gamma$$
$$0 \le \omega_{dk} \le 100 \quad \text{for } d = 1 \text{ to } 3 \text{ and } k = 1 \text{ to } 3$$

For Telemedicine goal model, by setting the goals to 70 and 80, the optimisation problem with the auxiliary variable γ :

$$\min_{\omega L} \gamma$$
$$s.t$$
$$0.4096 * \omega_{11} + 0.4096 * \omega_{21} + 0.1024 * \omega_{12} + 0.1024 * \omega_{22} - 70 \le \gamma$$
$$0.1024 * \omega_{11} + 0.512 * \omega_{21} + 0.4096 * \omega_{12} + 0.4096 * \omega_{22} - 80 \le \gamma$$
$$0 \le \omega_{dk} \le 100 \quad \text{for } d = 1 \text{ to } 2 \text{ and } k = 1 \text{ to } 2$$

The above multi-objective functions are solved by a programming code in IBM CPLEX tool to find the weights of the leaf softgoals and the weights are shown in Table 1.

Kids Youth counseling			Telemedicine		
Actor	Leaf SoftGoals	Weight	Actor	Leaf SoftGoals	Weight
Kids and Youth	Comfortableness with Service	1	Patient	Normal Life Style	1
	Anonymity	0.65		Quality of Care	0.67
	Immediacy	0.10			
Organisation	HighQualityCounseling	0.57	HealthCare Provider	Efficient Operations	0.99
	Immediacy	1		Effective Treatments	0.1
	Anonymity	0.1			
Counsellor	ListenforCues	0.1			

Table 1. Optimal weights for the Kids Youth Counseling and the Telemedicine case study

4.3 Evaluation of the Approach

The weights computed by the optimisation goal model are now used in the quantitative analysis described by Chitra et al.(2015) to find the alternative option that provides maximum satisfaction of the top softgoals. The top softgoals scores and the satisfaction comparison for the two goal models, Youth Counseling and Telemedicine, are given in Table 2. In this Table, it can be observed that the alternative *Use CyberCafe/Portal/ChatRoom* dominates the *Use Text Messaging* for Youth Counseling goal model and that the Telemedicine goal model, the alternative *Provider Centred Care* dominates the *Patient Centred Care*. To evaluate the effectiveness of the proposed optimal model, the scores computed from the softgoals optimisation, are compared with the leaf softgoals optimisation model. By using the leaf based optimal model, presented by Chitra et al. (2016), the objective functions are obtained for both case studies: Youth Counseling and Telemedicine. For these objective functions, the goal programming approach was applied to solve the weights of the leaf softgoals. Due to space restrictions, illustration is shown only for the Telemedicine case study. The goal programming based objective function for the case study Telemedicine is given as

$$\min_{\omega L} \gamma$$

$$s.t$$

$$0.64 * \omega_{11} + 0.64 * \omega_{21} + 0.16 * \omega_{12} + 0.16 * \omega_{22} - 70 \leq \gamma$$

$$0.16 * \omega_{11} + 0.81 * \omega_{21} + 0.64 * \omega_{12} + 0.64 * \omega_{22} - 80 \leq \gamma$$

$$0 \leq \omega_{dk} \leq 100 \quad \text{for } d = 1 \text{ to } 2 \text{ and } k = 1 \text{ to } 2$$

The weights of the leaf softgoals were found and used in the analysis of the alternative selection. The score comparisons are shown in Table 3 (Figure 5). It can be inferred from these tables that the proposed softgoals based optimisation model gives a better scores compared to the leaf softgoals optimisation model, with the exception of the top softgoal *Viable Healthcare Service* for the actor *Provider Centred Care*. Hence the softgoal optimisation model outperforms the leaf softgoal optimisation model. The scores obtained from the proposed approach were not compared with the approach without optimisation as the aim of the optimisation model is to avoid the subjective selection of weights for the leaf softgoals.

Kids Youth counseling				Telemedicine			
Actor	TopSoft Goals	Alternative option Score		Actor	Top Soft Goal	Alternative option Score	
		Use Text Messaging	Use CyberCafe /Portal/ChatRoom			Patient Centred Care	Provider Centred Care
Kids and Youth	Get Effective Help	90%	100%*	Patient	Happiness	99%	100%*
Organisation	Happiness	38%	98%*	HealthCare Provider	Viable Healthcare Service	37%	84%*
Counsellor	Help Kids	0 %	2%*				

Table 2. Scores of Top softgoals of the Kids Youth Counseling and the Telemedicine case study

Actor	Top Soft Goals	Patient Centred Care		Provider Centred Care	
		With Soft goals Optimisation	With Leaf Soft goals optimisation	With Soft goals Optimisation	With Leaf Soft goals Optimisation
Patient	Happiness	99%	99%	100%	30%
Healthcare Provider	Viable Healthcare Service	37%	24%	84%	89%

Table 3. Scores Comparison for the Telemedicine case study

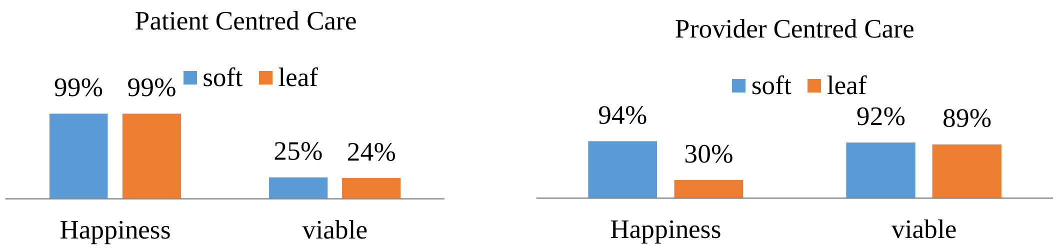

Figure 5. Comparison of Softgoals optimisation scores with Leaf softgoals Optimisation scores for Telemedicine case study

The main limitation of the proposed approach is that it can be applied to goal models when the alternative options are ‘OR’ related and cannot be applied when goals/task are ‘AND’ related.

5 CONCLUSION AND FUTURE WORK

Optimisation techniques have a significant part to play in the goal analysis of the goal models. This paper has demonstrated how multi-objective optimisation can help decision making among the alternative design choices. In particular, this paper presented a technique of representing a given *i** framework as multi-objective optimisation models. These models are then solved by the goal programming approach, used to compute the weights of the leaf softgoals of the given *i** framework. These weights are in turn used in the goal analysis to select the alternative that maximises the satisfaction of the top softgoals. A key feature of these models, as opposed to other optimisation models, is that objective functions are derived by considering all of the non-functional (softgoals) elements of the given system. The optimisation model is evaluated and the evaluation results are demonstrated using the case studies the Youth Counseling System and the Telemedicine System, taken from existing RE literature. The evaluation results showed that the softgoal based goal programming optimisation is an improvement on the existing optimisation model.

For future work, it is planned to develop a tool that will perform optimal goal programming based goal analysis; using this tool to conduct an empirical validation to check the feasibility of the proposed approach.

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